Race, Crime, and Police Pay: A Study in Compensating Wage Differentials

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This paper is an exploration of factors impacting police pay. The goal of this paper is to isolate the impact of crime on police pay to measure the compensating wage differential resulting from on-the-job danger for police officers (as measured by violent crime rates). In addition, the analysis allows the estimated compensating differential to vary with the race of the individual police officer as well as with the demographic composition of the police departments and populations served. Previous work on the determinants of police pay informs the analysis, including the empirical measures, regression specification, and control variables.

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Figure 1 is on page 9. This figure is a graph depicting the change in violent crime rates from period one to period two in relation to the violent crime rates in period one. This graph is included to demonstrate that there is not a significant reason to be concerned that there are distinct unobserved differences between metropolitan areas that experienced an increase in violent crime and those that experienced a decrease in violent crime over the interval.

CHAPTER ONE

Introduction

Police officers hold unique positions within their communities. Entrusted with protecting their citizens from harm, police officers not only must encounter on-the-job danger, but also remain directly responsible for charging headstrong in the direction of such danger. This aspect of the job is well understood not only by police officers, but also the greater community.

However, each metropolitan area carries its own level and variety of crime that its police are tasked to control. In some of these metropolitan areas, property crimes like theft are more common than violent crimes. In other areas, like college campuses, public intoxication and minor in possession charges are the mode for police-involved incidents.

When considering the different types of crimes police respond to as part of their jobs, it is plain to see that some crimes make policing an inherently more difficult job than others. In particular, when an area has a higher rate of violent crimes (murder, aggravated assault, rape, and robbery), policing the area carries more risk to police officers.

Just as with every job, policing involves wage and non-wage characteristics. Rational potential police officers in the labor market value the wage and non-wage characteristics in their utility functions and select the job in the location with the highest utility values available to them. Included among these non-wage characteristics is the danger level of the job potential police officers select.

This thesis focuses on how on-the-job danger, characterized by local violent crime rates, impacts police pay in major metropolitan areas in the United States. In addition, this thesis controls for factors that allow for differences between select groups to emerge if any significant differences exist in the data set.

Question

The primary question this thesis addresses is: Does danger impact police pay? This paper also examines how the potential effects of danger and returns to human capital gains vary across demographic groups.

Prior Work on Police Pay

Because this paper examines police pay, it is important to begin the study with a background understanding of what factors are critical to determining pay for police officers and forming the foundation of the model to use in this paper. In preparing to study police pay, I read a number of papers included in the bibliography of this thesis. The most critical source for building a model of police pay came from a paper entitled "Collective Bargaining Laws, Threat Effects, and the Determination of Police Compensation" written by Casey Ichniowski, Richard B. Freeman, and Harrison Lauer. In this paper, the author studied the effects of successful negotiations for police unions on their job success rate. This author's work provided the backbone for the model of human capital and demographic characteristics used in this paper.

Prior Work on Compensating Wage Differentials

Compensating wage differentials result from both a need to fill undesirable jobs and a distribution of willingness to take such a job in the labor market. If only a few undesirable vacancies need to be filled, then a compensating wage differential may be unnecessary or much lower than if a large number of people must be convinced to take an unsavory job. A critical informant for this paper's work on compensating wage differentials is the work of Thomas Deleire and Helen Levy and their paper "Worker Sorting and the Risk of Death on the Job." In this paper, I found my first understanding of how compensating wage differentials functioned in relation to labor market preferences of employees of different personal characteristics. In this paper, the authors discovered preferences for dangerous jobs were different depending on marital and parenthood statuses. For example, they discovered that men were more likely to take risky, higher-paying jobs if they had no children or if they were married with children than if they were single parents.

Prior Work on Underrepresentation in Police Forces

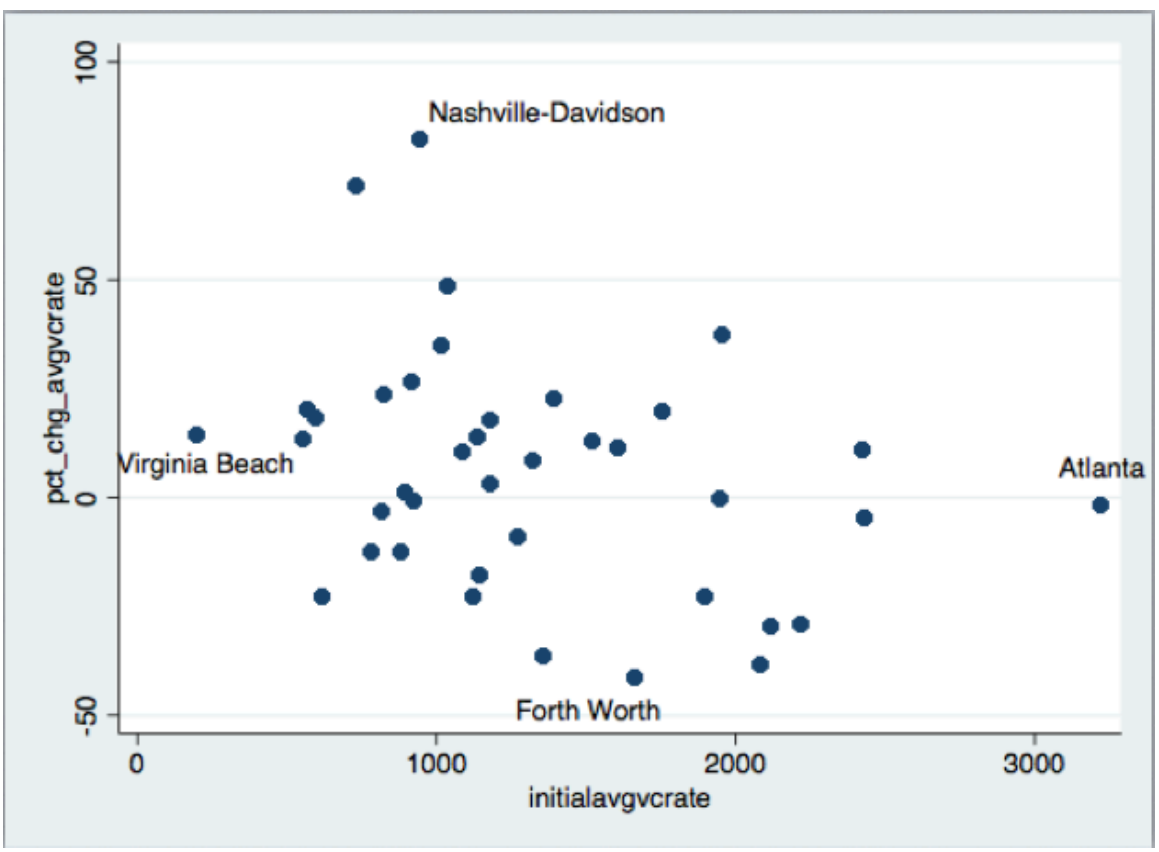
This paper's inclusion of a study of the potential impact of departmental demographics on pay and compensating wage differentials stems from my reading a diversity report on police and their communities from a report called "Diversity on the Force: Where Police Don't Mirror Communities" from the magazine *Governing*. In this report, major cities in the United States were assessed on their diversity representations and a critical indicator to evaluate these departments was the gap for different minority groups between population and police department representation.

Time Period and Metropolitan Area Selection

In this paper, the time period of interest is 1985-2000. Specifically, this thesis analyzes differences between wages in 1990 and 2000 for police and related occupational fields. The corresponding crime levels are the five-year periods of 1985-89 and 1995-99, respectively. I selected this time period because violent crime rates and changes in violent crime rates varied widely across cities with different characteristics. As shown below, there was a broad range of changes in violent crime rates among cities in the sample. In the entire sample, violent crime rates decreased from period one to period two, but for many of the metropolitan areas, the rates increased.

In Figure 1 below, the percent change in violent crime is graphed against the 1990 average (measured from 1985-89) to demonstrate that the changes in violent crime rates did not follow a strict pattern according to starting violent crime rates. In particular, the highest initial violent crime rate observed in the sample was in the Atlanta metropolitan area and the lowest initial violent crime rate observed was from the Norfolk-Virginia Beach metropolitan area. Both of these areas saw little to no change in their violent crime rates between period one and period two. The metropolitan areas with the greatest increase and decrease in their violent crime rates from period one to period two were Nashville-Davidson and Fort Worth-Arlington, respectively. Both of these metropolitan areas had violent crime rate near the average for period one. In all, there is a small trend downward for this graph, indicating that the metropolitan areas with higher starting crime rates experienced slightly lower increases or higher decreases in violent crime rates, on average. However, this is largely skewed by a few large cities like New York City sitting at a high initial violent crime rate and significant decrease from period one to period two.

FIGURE 1



In the interest of analyzing the finer details of any calculation of a compensating wage differential for police officers in the selected major metropolitan areas, this paper also examines the compensating wage differential values separately for black, white, and Hispanic individuals, as well as separately for males and females.

In addition, this thesis also tests for significance of a defined variable for the disparities of minority representations on police forces. The goal of this inclusion was to see if differences in the wages and compensating wage differentials were paid differently to departments that more and less nearly mirrored the racial composition of the city. However, this goal became more difficult to accomplish as a clear issue with endogeneity and omitted variable bias emerged for these indicators.

CHAPTER TWO

Compensating Wage Differentials

This paper applies the theory of compensating wage differentials in the labor market for police officers in major metropolitan areas in the United States. Compensating wage differentials allow for an understanding of the non-wage characteristics of jobs. When an individual chooses to accept a job, he must accept all characteristics of the job. The location, coworkers, noises, health benefits, and even smells of a job can all make a job more or less appealing to an individual than another job for equal pay.

One consequence of individuals' preferences varying among various job characteristics is that if two jobs both pay wage = w_0 at competitive equilibrium, but differ in a non-pay characteristic N, individuals will select the job with their preferred characteristic. In general, when considering jobs that pay C in wages (amount allowing for consumption) and have non-pay characteristic N, individuals maximize their Utility according to Eq. 1 and their individual alpha (α) based on their affinity (more negative value of α) or aversion (more positive value of α) to N.

$$Eq\ 1. \quad U = C - \alpha \times N$$

This means that if C is equal for two jobs, an individual will choose the job with more desirable non-pay characteristics to maximize utility. For example, if N represents a binary variable for the presence (N=1) of a loud, persistent noise at job 1 that is absent (N=0) at job 2, then the individual's preference for or against the loud, persistent noise at his place of employment determines which job yields him a higher utility. In the more obvious case in which the individual has a positive α value to indicate a desire to avoid such a noise, the utility from job 2 without the unpleasant noise exceeds the utility from job 1. This decision is shown below by comparing U_1 and U_2 (given that $\alpha > 0$).

$$Eq\ 2. \quad U_1 = C - \alpha \times (1) = C - \alpha$$

$$Eq\ 3. \quad U_2 = C - \alpha \times (0) = C$$

$$C > C - \alpha$$

$$\therefore$$

$$U_2 > U_1$$

However, when the two jobs pay different wages, individuals can rationally choose the job with the less desirable characteristic if the difference in C is large enough to compensate for non-wage components of the jobs. In particular, each individual's value for α determines the exact differential dollar amount that a job with the undesirable characteristic must pay to yield the same utility. Consider the loud noise example from above, but this time the two jobs pay different wages, C_1 for job 1 and C_2 for job 2. See below (with the same assumption that $\alpha > 0$).

$$U_1 = C_1 - \alpha \times (0)$$

$$U_2 = C_2 - \alpha \times (1)$$

$$U_1 = U_2 = C_1 = C_2 - \alpha$$

$$C_1 - C_2 = \alpha$$

When comparing two jobs with a binary (N = 0 or N = 1) condition for the non-pay characteristic of interest, the difference in compensation ($C_1 - C_2$) represents the compensating differential necessary to make the individual indifferent between the two jobs. In other words, the individual chooses the job with less desirable characteristics if and only if the difference in wage is greater than $C_1 - C_2$.

In this thesis, the non-pay aspect of interest is the violent crime rate in the metropolitan area. Individuals who consider and qualify for positions in police departments across the United States express different values of α in their employment decisions. However, while some individuals considering work as police officers may prefer to work in an area with a higher violent crime rate out of nobility or risk-seeking behavior, this thesis predicates that police officers in the aggregate will prefer to work in safer metropolitan areas hypothesizes that, accounting for other relevant factors, compensation should reflect an aversion to policing in areas with higher violent crime rates. Thus, wages should be higher to compensate for on-the-job danger of officers policing higher crime areas.

In this thesis, N is a continuous variable rather than a binary indicator. The next section will provide more specification about the qualifications of the data, but the importance of this distinction is that the compensating differential amount will not represent a simple amount necessary to overcome the binary presence of on-the-job danger. Instead, N indicates the degree of danger. With all metropolitan areas experiencing violent crime rates greater than zero, α will represent a coefficient for the degree of intolerance police officers perceive from a higher violent crime rate. Again, the assumption is that each individual in the dataset will have a unique value of α, but the regression methods reveal the compensating differential required for higher violent crime rates paid to the marginal worker considering a safer work alternative.

CHAPTER THREE

Covariates and Data Explained

Institute for Public Use of Microdata Series

The backbone of data in this thesis is from the 1990 and 2000 United States Census surveys, provided by the Integrated Public Use Microdata Series (IPUMS). This includes individual characteristics include such exogenous variables as educational attainment, sex, race, age, marital status, and metropolitan area of residence. In addition, the primary dependent variable of interest for this thesis – log of the hourly income from wages - can be sourced to data provided by the 1990 Census and 2000 Census from IPUMS.

From this backbone, the data was stripped to focus on individuals from metropolitan areas surrounding cities of at least 300,000 individuals in 1990. This limitation allowed for sufficient observations for meaningful examination from the metropolitan areas included and framed the study to focus on 51 metropolitan areas. Additionally, limitations were restricted to individuals in comparable occupational classes to police officers. To accomplish this restriction, observations were dropped if the individual was self-employed, worked for a private for-profit organization, private non-profit organization or the federal government, or if the worker's class was unpaid family labor. Federal employees were removed from the dataset because wage changes would likely not be affected by local conditions to any degree of significance.

Next, individuals were dropped from the dataset if they identified as "Not in Labor Force." These restrictions left local and state employees, including police officers that fell into these categories, from the metropolitan areas of the 51 most populous cities for the dataset. At this stage, to remove any potential unconventional members of the labor market and for the sake of simplicity, individuals outside the age window of 25-59 years were dropped from the sample.

After classifying experience levels into categories, educational levels were also categorized into meaningful variables. The omitted educational group was any education level below a high school diploma. The included groups in the sample were individuals with just a high school diploma, individuals with some college experience, individuals with a Bachelors degree, and individuals with some educational achievement beyond a bachelors degree. By categorizing these educational levels, this paper can assess the wage returns for various groups to reaching an additional level of education in comparison to not completing high school.

Categories for uniform indications of racial characteristics were made based on the Census data provided. Any individuals with non-zero values for the detailed Hispanic identification category qualified as Hispanic for this paper. Any individuals who did not fit that description and identified as "White" for the single race identification were categorized as "White" for this paper. Finally, any individuals who identified their singular race as "Black" were categorized as such for the purposes of this paper. As a result, any individual in the "White" category was only in this category, but there were some individuals who fell into both the "Hispanic" and "Black" categories. Originally a category was made for "Asian" individuals in the sample, but once Honolulu was removed from the sample for not fitting one of the later requirements, there were not any metropolitan areas left with "Asian" populations exceeding 20% in 1990 or 2000. As a result of this removal, all individuals who fell into neither the "White" nor the "Hispanic" nor the "Black" categories were classified as "Other" for this paper.

Once the individual demographic and human capital characteristics were categorized, individuals were classified as "police" if their jobs fell into a pool of occupational codes that were of interest for observing the impact of on-the-job danger. This category was primarily drawn from US Census occupational code 385, including police officers, campus police, and investigators. The category distinction was drawn to isolate individuals who would be at risk of exposure to on-the-job danger from work in the field.

Finally, from the data available from IPUMS and the job description categories available on the Census Bureau's website, a comparable job category called "administration" was created. This category was created for comparisons to be drawn with any observed qualities for individuals in the "police" job category. Individuals qualified for the "administration" category if their job was classified as administrative or secretarial in the occupational codes. These individuals were chosen as a comparable control groups because their jobs were assumed to be relatively isolated from on-the-job danger that would change as a result of local violent crime rates. In addition, these jobs were thought to be likely to follow similar educational returns trends to those of police officers.

FBI Uniform Crime Reporting

The second critical source of data for this thesis is the Uniform Crime Reporting Statistics publicly available from the Federal Bureau of Investigation. The Uniform Crime Reporting Statistics provided statistics to characterize the non-pay aspect of interest for this thesis. Violent crime rates per 100,000 residents and murder rates per 100,000 residents were both used at different points throughout this thesis to characterize on-the-job danger for police in the metropolitan area.

The figures selected were all chosen from the most local police authority available to the metropolitan area. For all of the cities chosen, this authority was the city or metropolitan police force. Any cities that lacked data available for any year between 1985 and 1989 or 1995 and 1999, inclusive at the extremities, were considered unusable for the purposes of this paper. Any individuals left in the sample from these metropolitan areas were removed from the data set. This restriction left 41 metropolitan areas with all of the data available to use in this paper. The one exception to this rule is that Baltimore did not have murder rates available for 1999, but was left in the sample because its residents had been used for all of the regression analysis for violent crime total rates earlier in the thesis.

Once the data was limited to observations from metropolitan areas with data available for all years, the averages were taken over the first five-year period (1985-89) for observations from the 1990 Census and over the second five-year period (1995-99) for observations from the 2000 Census. Again, attention was paid to Baltimore's murder rates to average by dividing by four instead of five for its period two observations. The logarithms of these averages were taken so that interpretations of any significance could be drawn in relation to a 1% increase in violent crime (or murder) rates in a meaningful way.

Law Enforcement Management and Administrative Statistics

The final significant data source came from the Law Enforcement Management and Administrative Statistics from the Bureau of Labor Statistics for the United States. These surveys are administered periodically to assess various characteristics and practices of local police departments in the United States.

Using the surveys administered in 1990, values were added to the dataset for the demographic composition of the police departments for each metropolitan area as a freeze-frame of the situation in 1990. Ideally, values from the 2000 survey would be available with which to compare these characteristics to assess the impact of increasing or decreasing diversity on any of the outcomes of interest. However, the data from the Law Enforcement

Management and Administrative Statistics was sporadic and not comparable from year-to-year in terms of which departments (city vs. county primarily) were surveyed and what data was collected.

Cross-referencing the demographic data with the population demographic data available from the Census Bureau, measures could be made for the disparities between Black representation in local populations and in local police departments. The same figures could be calculated for Hispanic representation. In almost all metropolitan areas, both of these groups were significantly underrepresented in police departments, with the average underrepresentation for Black populations in their police force being 11% and the average underrepresentation for Hispanic populations in their police force being 6%.

Model

Putting all of this data together, the model for this paper forms from variables expected to be associated with pay levels for police. The model for this thesis is below in Equation 4. The predicted log of the hourly wage for an individual in the sample is estimated by five input terms. In particular, the dependent variable in Equation 4 represents the natural logarithm of hourly earnings for individual i in metropolitan area m and in Census year t.

The first input term is the demographic and human capital characteristics of the individual in the sample. This term includes the individual's age (proxy for experience), educational attainment level, gender, race, and occupational category (police or administrative or neither).

The second term is the impact of local violent crime rates, observed for individuals in the full sample, administrative, and police categories. The null hypothesis for this term is that the slope would be statistically insignificant from zero for all three groups. The alternative hypothesis is that the slope is significantly larger than zero for the police group.

The third term in the model is the fixed effects for the metropolitan area and for the police departments. In this paper, the fixed effects to notice are the demographic disparity indicators from the LEMAS surveys and the distinctions between wages that are naturally created by different attractions of different cities.

The fourth term captures the time-fixed effects in this sample. These effects range from what stage of the business cycle in which these samples were taken from the Census Bureau to general increases in wages throughout the period of observation.

The fifth term is the error resulting from unobserved variations in the individual, metropolitan area, and time period characteristics that also impact individual wages. This term is expected to have a large impact because so much of the impact of wage data is not captured in this paper.

$$Eq\ 4. \quad \log(\widehat{hrwage})_{\imath mt} = \beta x_{imt} + \gamma C_{mt} + \alpha_m + \pi_t + \epsilon_{imt}$$

CHAPTER FOUR

Data

The data for this paper is sourced from IPUMS, the Uniform Crime Reporting Statistics from the FBI, and the Law Enforcement Management and Administrative Statistics surveys from the Bureau of Labor Statistics. The tables in this section display OLS regression outcomes for significance of slopes for each independent variable listed while holding the others constant. In every regression run, the errors were clustered by year and by metropolitan area. In addition, indexing was performed to account for much of the metropolitan fixed effects on wages from local conditions.

In Table 1 below, the first interacted regression yields statistically significant slopes for public employees in the full sample selected for this paper at all increasing levels of age (proxy for experience from Census data) and educational attainment. The omitted group for experience level is the age group 25-29 and the omitted educational attainment group is individuals with education levels less than a high school diploma. To clarify what the specific values indicate, the first listed slope under "Public Employees" in Row 1 is 0.114, meaning that individuals in this sample earning 11.4% more for having an experience level in the age window of 30-34 years when compared with individuals aged 25-29. In addition, this value is statistically significant from zero at a 5% level so the slope is marked with two asterisks. In fact with a standard error – listed parenthetically below the slope – of 0.007, the significance level for this slope estimate is significant at a 1% level as well.

Critical to Table 1 is that the slope estimates under "Police Extra" is the deviation for individuals in the sample marked as "police." These individuals are specified in Chapter Three according to restrictions made to focus on individuals most likely to fit the goal of this paper – to assess the wages of police individuals in relation to on-the-job danger. In a separate table, police totals will be compared with those of other occupational groups, but for Table 1, the focus is on the deviations of police pay from the returns and calculations of pay for other occupations in the same public, local and state sector of the economy.

TABLE 1

LOGHRWAGE	*With All & Interactions (N = 331,749)* Public Employees	Police Extra
1. Age 30-34	0.114** (0.007)	0.020 (0.019)
2. Age 35-39	0.204** (0.008)	0.045** (0.022)
3. Age 40-44	0.248** (0.009)	0.051** (0.022)
4. Age 45-49	0.301** (0.009)	-0.010 (0.024)
5. Age 50-54	0.332** (0.010)	-0.021 (0.024)
6. Age 55-59	0.334** (0.010)	-0.067* (0.035)
7. HS Diploma	0.154** (0.010)	0.075* (0.042)
8. Some College	0.293** (0.009)	0.072 (0.047)
9. Bachelors	0.520** (0.009)	-0.063 (0.047)
10. Grad School	0.717** (0.010)	-0.200** (0.053)
11. Black	-0.026** (0.009)	-0.084** (0.017)
12. Hispanic	-0.063** (0.012)	0.020 (0.013)
13. Other_Race	-0.071** (0.009)	-0.060 (0.043)
14. Female	-0.213** (0.007)	0.000 (0.021)
15. Year 2000	0.275** (0.005)	0.150** (0.021)
16. Log_Avg_ViolCrimeRt	0.019 (0.022)	-0.022 (0.025)
17. Police	0.183 (0.189)	X X
18. Black_Gap	0.036** (0.006)	0.000 (0.001)
19. Hispanic_Gap	-0.047** (0.005)	-0.002 (0.002)

In Table 2, the same figures and regression form the table, but lists the summed slope for police officers instead of listing the "Police Extra" to compare police to the group next to each other. The left column lists the slopes for each of the independent variables for the regression for the entire sample, including police. The right column lists the same but for just the police in the sample.

TABLE 2

LOGHRWAGE	*With All & Interactions (N = 331,749)* **Public Employees**	**Police**
1. Age 30-34	0.114** (0.007)	0.134**
2. Age 35-39	0.204** (0.008)	0.249** (+)
3. Age 40-44	0.248** (0.009)	0.299** (+)
4. Age 45-49	0.301** (0.009)	0.291**
5. Age 50-54	0.332** (0.010)	0.311**
6. Age 55-59	0.334** (0.010)	0.267**
7. HS Diploma	0.154** (0.010)	0.079**
8. Some College	0.293** (0.009)	0.221**
9. Bachelors	0.520** (0.009)	0.457**
10. Grad School	0.717** (0.010)	0.517** (-)
11. Black	-0.026** (0.009)	-0.110** (-)
12. Hispanic	-0.063** (0.012)	-0.043**
13. Other_Race	-0.071** (0.009)	-0.131**
14. Female	-0.213** (0.007)	0.213**
15. Year 2000	0.275** (0.005)	0.425**
16. Log_Avg_ViolCrimeRt	0.019 (0.022)	-0.003
17. Police	0.183 (0.189)	0.183
18. Black_Gap	0.036** (0.006)	0.036**
19. Hispanic_Gap	-0.047** (0.005)	-0.049**

In Table 3 below, the impacts and returns for pay are included separately for men and for women to observe any potential distinctions in the returns to experience, education, or the potential compensating wage differential for danger paid to each group.

TABLE 3

LOGHRWAGE	*With All & Police Interactions (N = 141,456) Male*		*With All & Police Interactions (N = 190,293) Female*	
	Full Sample	**Police Extra**	**Full Sample**	**Police Extra**
1. Age 30-34	0.140** (0.09)	0.003 (0.023)	0.100** (0.007)	0.006 (0.039)
2. Age 35-39	0.262** (0.011)	0.007 (0.030)	0.169** (0.008)	-0.004 (0.031)
3. Age 40-44	0.334** (0.011)	-0.009 (0.030)	0.197** (0.009)	-0.022 (0.040)
4. Age 45-49	0.397** (0.012)	-0.079** (0.030)	0.247** (0.008)	-0.078** (0.036)
5. Age 50-54	0.428** (0.014)	-0.088** (0.030)	0.281** (0.011)	-0.093** (0.043)
6. Age 55-59	0.428** (0.013)	-0.133** (0.046)	0.288** (0.010)	-0.115** (0.048)
7. HS Diploma	0.179** (0.011)	0.072 (0.055)	0.152** (0.011)	0.062 (0.081)
8. Some College	0.302** (0.011)	0.082 (0.059)	0.300** (0.012)	0.007 (0.084)
9. Bachelors	0.415** (0.010)	0.040 (0.062)	0.600** (0.012)	-0.165** (0.079)
10. Grad School	0.576** (0.010)	-0.046 (0.059)	0.825** (0.014)	-0.413** (0.129)
11. Black	-0.124** (0.012)	-0.016 (0.017)	0.040** (0.008)	-0.098** (0.029)
12. Hispanic	-0.067** (0.014)	0.057** (0.015)	-0.027 (0.008)	0.011 (0.024)
13. Other	-0.112** (0.012)	-0.002 (0.048)	-0.023** (0.011)	-0.055 (0.058)
14. Female	X X	X X	X X	X X
15. Year 2000	0.250** (0.005)	0.015 (0.018)	0.290** (0.06)	0.325** (0.023)
16. Log_Avg_ViolCrmRt	0.032** (0.024)	-0.040 (0.034)	-0.001 (0.023)	0.015 (0.029)
17. Police	0.435* (0.261)	X X	-0.099 (0.208)	X X
18. Black_Gap	0.040** (0.006)	0.001 (0.001)	0.036** (0.006)	-0.001 (0.002)
19. Hispanic_Gap	-0.047** (0.006)	-0.000 (0.002)	-0.047** (0.005)	-0.004** (0.002)

Table 4 is the primary data table for the thesis. In this data table, the variables of interest were interacted with the two occupational codes to demonstrate any deviations specific to these two occupations. The goal of this table is observe police pay characteristics in the context of other public-sector local occupations with similar requirements, but no direct exposure to violent crime rates.

TABLE 4

LOGHRWAGE	*OLS Regression with Metropolitan Index (N = 331,749 & 82 Clusters for S.E)*		
	Full Sample	**Admin Extra**	**Police Extra**
1. Age 30-34	**0.119**** (0.006)**	-0.019* (0.010)	0.015 (0.019)
2. Age 35-39	**0.216**** (0.007)**	**-0.042**** (0.014)**	0.033 (0.022)
3. Age 40-44	**0.260**** (0.007)**	**-0.042**** (0.018)**	0.037 (0.022)
4. Age 45-49	**0.316**** (0.007)**	**-0.074**** (0.015)**	-0.027 (0.024)
5. Age 50-54	**0.348**** (0.009)**	**-0.089**** (0.016)**	-0.037 (0.024)
6. Age 55-59	**0.351**** (0.009)**	**-0.087**** (0.012)**	**-0.082**** (0.034)**
7. HS Diploma	**0.141**** (0.008)**	-0.008 (0.029)	**0.085**** (0.042)**
8. Some College	**0.274**** (0.007)**	-0.044 (0.032)	0.087* (0.047)
9. Bachelors	**0.526**** (0.009)**	**-0.195**** (0.035)**	-0.067 (0.046)
10. Grad School	**0.725**** (0.010)**	**-0.216**** (0.027)**	**-0.200**** (0.052)**
11. Black	-0.017* (0.009)	**-0.031**** (0.011)**	**-0.087**** (0.017)**
12. Hispanic	**-0.062**** (0.012)**	**0.043**** (0.011)**	0.025* (0.013)
13. Other_Race	**-0.066**** (0.009)**	0.037 (0.023)	-0.052 (0.042)
14. Female	**-0.196**** (0.005)**	**-0.080**** (0.018)**	0.008 (0.018)
15. Year 2000	**0.299**** (0.005)**	**-0.146**** (0.014)**	**0.224**** (0.017)**
16. Log_Avg_ViolentCrimeRt	0.011 (0.021)	0.032* (0.018)	-0.026 (0.022)

Table 5 covers the next two pages with the same comparisons as Table 4, but divided to focus on the distinctions between White, Black, and Hispanic individuals and to include indicators for the predictive input of the gap indicators for demographic representation of minority groups in the police department. These values are indicated in columns 16 and 17. For clarification, the variable “Black Gap” refers to the percentage of the police department that is Black minus the percentage of the population that is Black. The same description but for Hispanic individuals and officers describes the variable “Hispanic Gap.”

TABLE 5

LOGHRWAGE		1. Age 30-34	2. Age 35-39	3. Age 40-44	4. Age 45-49	5. Age 50-54	6. Age 55-59	7. HS Diploma	8. Some College
OLS with Metropolitan Index (N = 230,581 & 82 Clusters) White, Non-Hispanic	**Police**	0.014 (0.021)	0.039* (0.034)	0.039 (0.025)	-0.009 (0.026)	-0.015 (0.027)	-0.050 (0.041)	0.010 (0.052)	-0.013 (0.055)
	Admin	-0.015 (0.011)	**-0.041**** **(0.015)**	**-0.043**** **(0.016)**	**-0.068**** **(0.015)**	**-0.093**** **(0.016)**	**-0.073**** **(0.015)**	-0.007 (0.028)	-0.047* (0.028)
	Full	**0.123**** **(0.006)**	**0.222**** **(0.008)**	**0.269**** **(0.008)**	**0.322**** **(0.008)**	**0.359**** **(0.009)**	**0.360**** **(0.009)**	**0.111**** **(0.009)**	**0.249**** **(0.010)**
OLS with Metropolitan Index (N = 28,023 & 82 Clusters) Hispanic	**Police**	0.017 (0.038)	**0.110**** **(0.044)**	**0.108**** **(0.051)**	**0.077*** **(0.043)**	-0.050 (0.084)	-0.022 (0.091)	0.272* (0.151)	**0.329**** **(0.133)**
	Admin	-0.003 (0.031)	0.043 (0.035)	-0.015 (0.031)	-0.004 (0.041)	0.007 (0.059)	0.031 (0.047)	-0.002 (0.057)	-0.031 (0.063)
	Full	**0.098**** **(0.014)**	**0.167**** **(0.013)**	**0.200**** **(0.013)**	**0.240**** **(0.015)**	**0.262**** **(0.014)**	**0.247**** **(0.016)**	**0.188**** **(0.020)**	**0.302**** **(0.014)**
OLS with Metropolitan Index (N = 61,474 & 82 Clusters) Black	**Police**	0.038 (0.037)	0.007 (0.035)	0.033 (0.039)	**-0.114**** **(0.043)**	-0.081* (0.045)	**-0.177**** **(0.071)**	0.103 (0.085)	0.091 (0.088)
	Admin	-0.034* (0.019)	**-0.056**** **(0.021)**	-0.020 (0.031)	**-0.103**** **(0.027)**	**-0.085**** **(0.030)**	**-0.163**** **(0.033)**	0.041 (0.037)	0.003 (0.047)
	Full	**0.100**** **(0.012)**	**0.201**** **(0.011)**	**0.237**** **(0.014)**	**0.315**** **(0.013)**	**0.328**** **(0.015)**	**0.339**** **(0.017)**	**0.129**** **(0.013)**	**0.253**** **(0.010)**

LOGHRWAGE		9. Bachelors	10. Grad School	11. Black	12. Hispanic	13. Female	14. Year 2000	15. Log_Avg_VioCrmR	16. Black Gap	17. Hispanic Gap
OLS with Metropolitan Index (N = 230,581 & 82 Clusters) White, Non-Hispanic	**Full**	**0.492** (0.010)**	**0.692** (0.012)**	X X	X X	**-0.222** (0.006)**	**0.297** (0.005)**	-0.010 (0.020)	**0.036** (0.006)**	**-0.049** (0.005)**
	Admin	**-0.198** (0.029)**	**-0.216** (0.027)**	X X	X X	**-0.068** (0.014)**	**-0.139** (0.016)**	**0.040** (-0.021)**	0.001* (0.001)	**-0.006** (0.002)**
	Police	**-0.135** (0.055)**	**-0.270** (0.066)**	X X	X X	-0.004 (0.023)	**0.205** (0.018)**	-0.021 (0.027)	0.000 (0.001)	-0.003 (0.002)
OLS with Metropolitan Index (N = 28,023 & 82 Clusters) Hispanic	**Full**	**0.598** (0.022)**	**0.785** (0.021)**	-0.012 (0.013)	X X	**-0.184** (0.009)**	**0.307** (0.007)**	-0.001 (0.023)	**0.026** (0.008)**	**-0.030** (0.005)**
	Admin	**-0.171 (0.069)**	**-0.203** (0.079)**	-0.041 (0.040)	**-0.871** (0.233)**	**-0.082** (0.027)**	**-0.123** (0.025)**	**0.163** (0.033)**	0.004* (0.002)	**-0.006** (0.002)**
	Police	0.125 (0.121)	-0.110 (0.181)	-0.021 (0.045)	-0.432 (0.262)	**0.058** (0.028)**	**0.318** (0.031)**	0.015 (0.034)	0.001 (0.002)	0.001 (0.002)
OLS with Metropolitan Index (N = 61,474 & 82 Clusters) Black	**Full**	**0.534** (0.016)**	**0.750** (0.016)**	X X	**-0.067** (0.016)**	**-0.113** (0.007)**	**0.298** (0.008)**	**0.062** (0.022)**	**0.025** (0.009)**	**-0.040** (0.008)**
	Admin	**-0.162** (0.057)**	**-0.203** (0.056)**	0.260* (0.141)	0.054 (0.047)	**-0.076** (0.012)**	**-0.163** (0.019)**	0.002 (0.018)	-0.000 (0.001)	-0.002 (0.002)
	Police	-0.042 (0.096)	**-0.213** (0.101)**	0.189 (0.195)	0.093 (0.059)	-0.001 (0.017)	**0.233** (0.030)**	-0.037 (0.026)	-0.000 (0.001)	-0.000 (0.002)

CHAPTER FIVE

Findings

From the data in the tables from OLS regressions performed to create Chapter Four, there are five primary takeaways.

The first main takeaway is the absence of an observed compensating wage differential for any police demographic. As shown in Table 4, the full sample, police and administrative individuals did not experience an increase in pay for an increase in violent crime rates at the 5% significance level. In fact, the only group to experience an increase statistically significant at the 10% level was the administrative group, chosen to be the control group least exposed to on-the-job danger.

The second takeaway from this data is the dramatic increase in police wages, even controlling for general increase in wages in this sector of the economy as well, that occurred from 1990 to 2000. While wages in the local and state public employees included in the sample rose by an average of 29.9% according to Row 15 in Table 4, police salaries rose 22.4% on top of that already high amount. That means that police salaries rose 52.3% on average from 1990 to 2000. For comparison, individuals in administrative positions only saw their salaries increase by 15.3% over the same interval.

The third takeaway from the data in Chapter Four is the lack of variation between demographic groups for the possible observance of a compensating wage differential as well. While the returns to education and experience for police officers vary between White, Black, and Hispanic individuals, with White individuals receiving higher returns to experience at every age group and most educational attainments, there were no distinctions in terms of compensating wage differentials for officers of different demographic characteristics – including race and gender.

The fourth takeaway from this thesis is that there was not a significant difference in the slopes and still no observed compensating wage differential for police when murder rates were used as the indicator for danger instead of total violent crime rates.

The fifth takeaway is that the gap statistics observed are statistically significant in the regressions. These measures do not vary significantly for white/black/Hispanic police and carry through for all occupations in the local and state public sector – i.e. police are not special in this sense.

CHAPTER SIX

Implications and Limitations

This thesis has a number of general shortcomings. In each regression this paper has run, roughly 30% of the variation in logarithm of the hourly wage has been explained by the variation in the included x variables, indicating a need for significant caution when drawing conclusions from the data available. In selecting individuals to correspond with violent crime rates for major cities in the United States, I was only able to reliably pinpoint individuals to their metropolitan area from the data available from the Censuses of 1990 and 2000. This overlap inconsistency between city and metropolitan area for data association could have muddied the waters for local impact because many suburban areas included in major metropolitan areas are actually insulated from the city's violent crime rates.

The first finding in Chapter Five is the lack of an observed compensating wage differential in the data observed. While some of this may be due to the fact that there was an overlap issue in the data available from IPUMS, much of this observation may be from individuals with high abilities self-selecting into safer areas over the interval for the paper. These individuals would be receiving higher wages for their higher skills, but would be concentrated in areas with lower violent crime rates. It is possible that with the attention to high violent crime rates around the interval of this paper many individuals could have made this selection. A potential further direction in finding a compensating wage differential for police could involve more detailed observations and attempts at including police skill in the model. Perhaps arrest rates could be an indication of abilities.

This paper's second finding about the discrepancies in the wage increases between 1990 and 2000 for individuals in the different occupational categories is perhaps the most interesting statistic in Table 4. This discrepancy may be the result of the 1994 Violent Crime

Prevention and Law Enforcement Act, passed under President Clinton during the year of the highest violent crime rates in many of the major cities in the United States, according to FBI Uniform Crime Reporting Statistics.

Chapter Five's third finding addresses one of the primary goals of this thesis in discovering any fine differences between police pay determinants for officers of different demographic groups. Even by observing no compensating wage differential for the sample as a whole, it could have been the case that preferences were different among groups or that discrimination forced different individuals to accept a higher or lower compensating wage differential, which could have been statistically significant for one of the groups observed. However, it was not so. The only significant difference for police in Table 5 is the 8% lower wage for Black police officers when compared to their already discriminatorily lower pay in the full sample. As a possible new direction, research could dive into finer details to see if there are any more specific groups that do receive an observed compensating wage differential.

In addressing the fourth finding of this paper, it is possible that neither murder nor total violent crime rates were the proper indictor for police considerations of on-the-job danger. It would be helpful to see additional research performed that highlights risks such as police-involved shootings or maybe gender-based focuses on the impacts of rape statistics on police pay with a broader range of cities used on a larger scale to see any noticeable impacts that may exist.

In interpreting the fifth finding from Chapter Five, explanations could range from the belief that police representation can act as a proxy for local representation to regional demographic differences. Since there were no statistically significant across the board and that there is unequal tax collection and distribution across the board or the – much more likely – explanation that this was observed from omitted variable bias of locational trends of minority population concentrations (need a high concentration to be massively underrepresented on a police force). This explanation is much less compelling than the regional differences explanation, however.

First, the differences observed exist not just in the police departments. Second, having a highly unrepresentative police department in this paper requires a high floor of the minority population, which disproportionately occurred in lower-income areas in general for Black populations, particularly in Southern cities and in higher-income areas for Hispanic populations, particularly on the West Coast. Third, . Therefore, it is more plausible that these observed disparities are an issue of improper accounting for endogeneity with the population distributions in the metropolitan areas or omitted variable bias for regional importance in addition to specific metropolitan characteristics.

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